Hdr-CIELAB and Hdr-IPT: Simple Models for Describing the Color of High-Dynamic-Range and Wide-Color-Gamut Images

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Abstract

◆ Proposed method

- hdr-CIELAB and hdr-IPT
  - Addressing HDR questions
    - Hard intercepts at zero luminance/lightness
    - Uncertain applicability for color brighter than diffuse white
  - Replacing the power-function nonlinearities in CILAB and IPT with a more physiologically plausible hyperbolic function
    - Michaelis-Menten equation

Introduction

◆ Color space

– CIELAB

- Derived for applications with reflecting colored objects under a single uniform illumination
- Not derived for HDR stimuli
  - – Range in luminance/lightness from many orders of magnitude below diffuse white to many orders-of-magnitude above diffuse white
- Troubling the colorimetric calibration and characterization of HDR display systems

- IPT color space
  - Predicting constant hue angle for stimuli of constant perceived hue significantly better than CIELAB
  - Useful for gamut mapping algorithm
    - Aim to preserve perceived hue

◆ Proposed method

- Two modified color spaces
  - hdr-CIELAB and hdr-IPT
    - Beginning to address some of the problems of HDR colorimetry
- Basic structure of two color space
  - Replace power-function-based compressive nonlinearities with sigmoidal functions
    - More physiologically plausible
    - Well-behaved at extreme high and low relative luminance levels

Derivation and Formulation of hdr-CIELAB

◆ Derivation of hdr-CIELAB

$$f(\omega) = 100 \frac{\omega^{\varepsilon}}{\omega^{\varepsilon} + 0.184^{\varepsilon} + 0.02} \quad (1)$$

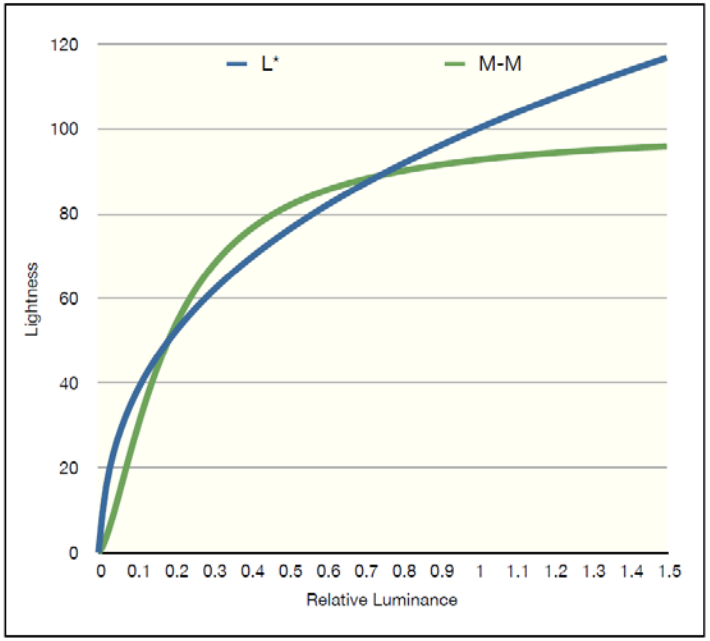

Fig. 1. CIELAB L* and fitted Michaelis-Menten functions of relative luminance in the range from 0-1.5.

Derivation and Formulation of hdr-IPT

– Goal of proposed algorithm
  - Transferring the color palette between two images
  - Allowing the user to control the amount of matching in a simple way

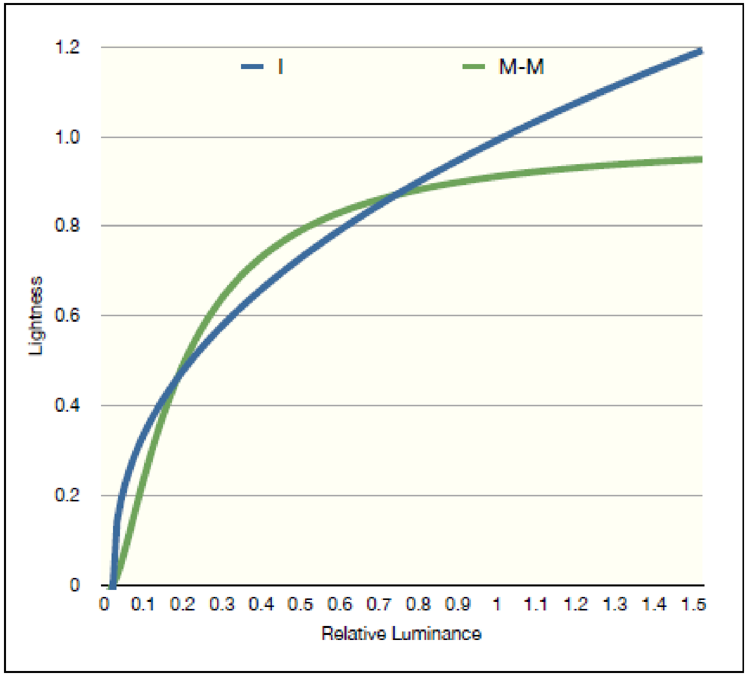

Fig. 2. IPT I and fitted Michaelis-Menten functions of relative luminance in the range from 0-1.5.

◆ Background

– Histograms

$$B = \left\lceil \frac{\max(I) - \min(I)}{V} \right\rceil \tag{2}$$

$$h(i) = \sum_{p=1}^{N} P(I(p), i), \qquad i \in [1, B] \tag{3}$$

$$v(i) = \min(I) + (i-1)V \tag{4}$$

$$P(I(p), i) = \begin{cases} 1 & i = \left\lfloor \dfrac{I(p) - \min(I)}{V} + 1 \right\rfloor \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where H is the set of all pairs $(h(i), v(i))$ for all $i \in [1, B]$ corresponding to the number of elements and values of the i bin of the histogram, and $I(p)$ is the value of the pth pixel of image I which contains to total of N pixels and $P(I(p), i)$ represents the probability of a pixel $I(p)$ belonging to a bin i.

– Bilateral filtering

- Smoothing regions in the image while respecting strong edges

$$I_{\text{bilat}}(p) = \frac{\sum_{q \in N} f(q-p)\, g\big(I(q) - I(p)\big)\, I(q)}{\sum_{q \in N} f(q-p)\, g\big(I(q) - I(p)\big)} \qquad (6)$$

where $I_{\text{bilat}}(p)$ is the output of the bilateral filter for the pth pixel of image I, and f, g are Gaussians operating on pixel distances and intensities respectively.

Appearance Predictions of Munsell Colors

- Lightness
  - Computing each scale for the target histogram
    - Removing high frequency details of the histogram
    - Preserving prominent feature
    - Use of downsampling and upsampling the original histogram
    - Maximum number of scales

$$S_{\max} = \left\lfloor \log_2 \left(\frac{B}{B_{\min}} \right) \right\rfloor \quad (7)$$

where B is the number of bins, and
$B_{\min}$ is the minimum allowed histogram size.

– Detecting features in each scale of the histogram
  - Appropriate way
    - Locating zero-crossings in the first-order derivatives of the histogram

$$\nabla h_{t,k} = h_{t,k}(i) - h_{t,k}(i+1), \qquad i \in [1, B_{k-1}] \tag{8}$$

    - Classifying zero-crossings as minima or maxima
      » Use of the corresponding values of the second-order derivative
    - Dividing the target histogram into a set of regions
      » Using the detected minima

$$R_{\min,k} = \{ i \mid \nabla h_{t,k}(i) \nabla h_{t,k}(i+1) < 0 \wedge \nabla^2 h_{t,k}(i) > 0 \} \tag{9}$$

where $R_{\min,k}$ is the set of minima for a scale k.

– Reshaping each corresponding region of the source histogram

- Bounds [a, b] of a region j

$$a = R_{\min,k}(j)$$

$$b = R_{\min,k}(j+1) - 1$$

- Mean and standard deviations of each region

$$\mu_{s,k}(j) = \sum_{i=a}^{b} \frac{h_{s,k}(i)}{b-a} \quad (10)$$

$$\sigma_{s,k}(j) = sqrt \sum_{i=a}^{b} \frac{\left(h_{s,k}(i) - \mu_{s,k}(j)\right)^2}{b-a} \quad (11)$$

where $\mu_{s,k}(j)$ and $\sigma_{s,k}(j)$ are the mean and standard deviation of the jth region of $H_{s,k}$, respectively.

- Reshaping the bins of corresponding regions

$$h_{o,k}(i) = \left(h_{s,k}(i) - w_{s,k}\mu_{s,k}(j)\right)\frac{w_{t,k}\sigma_{t,k}(j)}{w_{s,k}\sigma_{s,k}(j)} + w_{t,k}\mu_{t,k}(j) \qquad (12)$$

where $h_{o,k}$ is the set of output histogram bin counts for a given scale k, and $w_{s,k}$ is a weight dependent on k, with $w_{t,k} = 1 - w_{s,k}$.

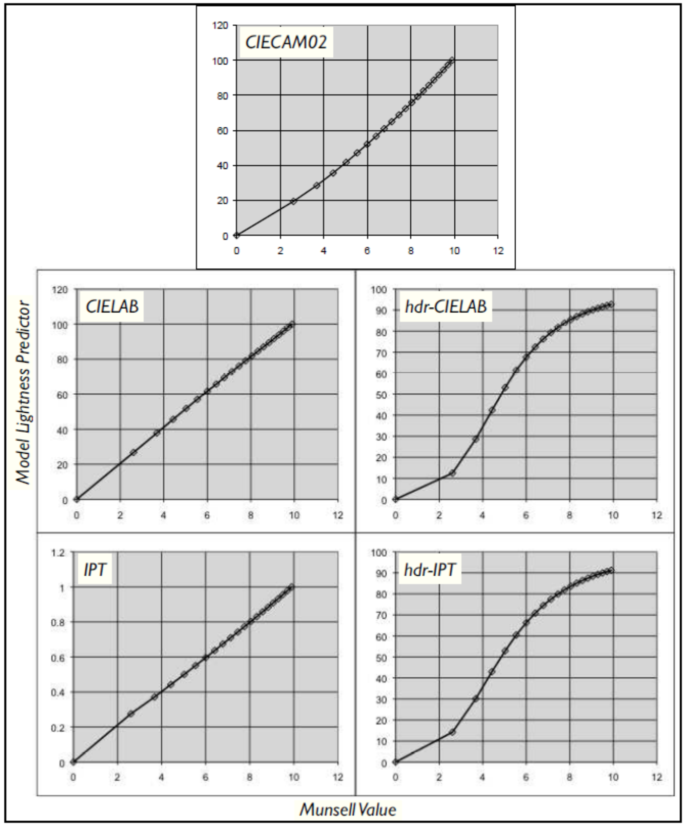

Fig. 3. Model lightness predictors as a function of Munsell Value.

– Applying an additional match of means and standard deviations

- First transfer between histograms
  - Taking into account the features of the target
- Second transfer
  - Considering features of the source

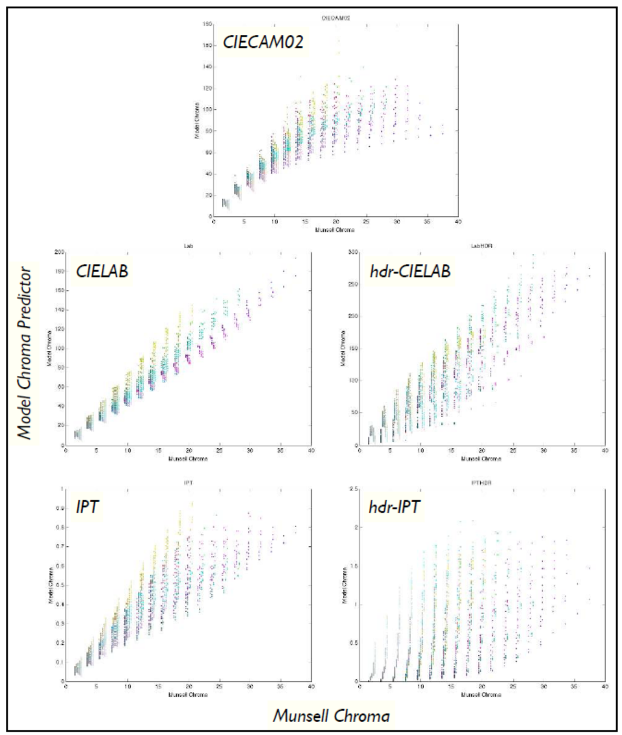

Fig. 4. Model chroma predictors as a function of Munsell Chroma.

◆ Chroma

– Creating output image through full histogram matching

- Use of the source image and the reshaped histogram
- Cumulative histograms

$$C_s(j) = \sum_{i=1}^{j} h_s(i), \quad j = 1, \ldots, B \tag{13}$$

$$C_o(j) = \sum_{i=1}^{j} h_o(i), \quad j = 1, \ldots, B \tag{14}$$

$$I_o(p) = v_0\left(C_o^{-1}\left(C_s\left(\frac{I(p) - \min(I) + 1}{V}\right)\right)\right) \tag{15}$$

where a cumulative histogram C is defined as a function mapping a bin index to a cumulative count, and
the inverse function C^{-1} acts as a reverse lookup on the histogram, returning the bin index corresponding to a given count.

◆ Hue Linearity

– Example of partial matches between two HDR images

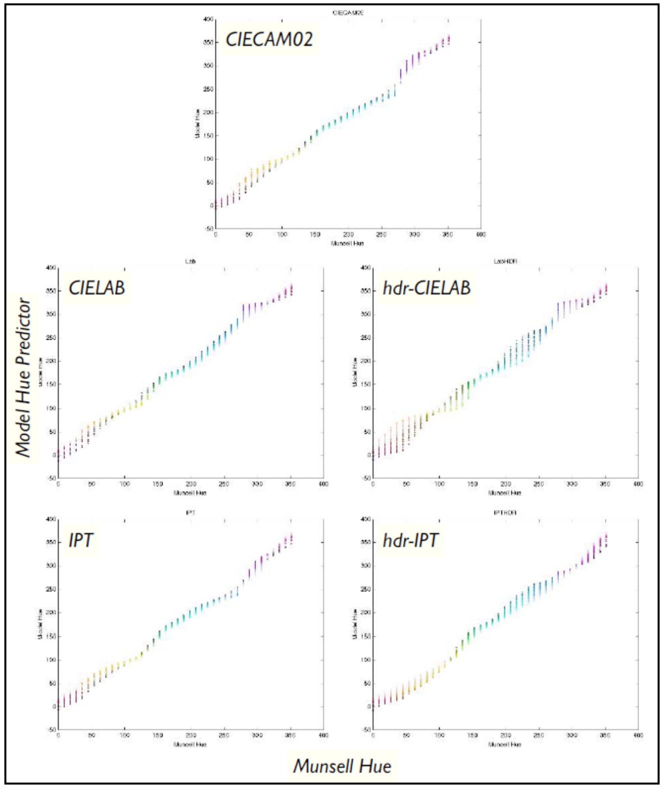

Fig. 5. Model hue predictors as a function of Munsell Hue.

– Comparison with color transfer between paris of HDR images

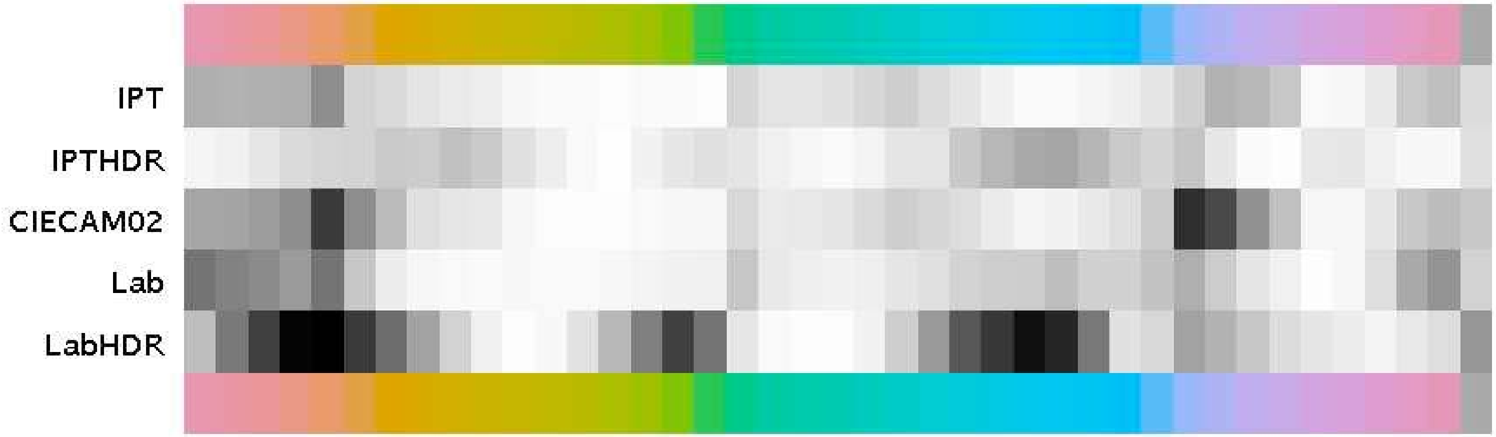

Fig. 6. Visualization of PCA analysis on the dimensionality of constant hue lines. Dark entries indicate that a significant amount of variation requires two dimensions to describe (an indication of hue nonlinearity).

◆ Hue Spacing

– Manipulating local contrast in the resulting image

- Use of the bilateral filter
- Manipulating the residual after subtracting the filtered image

$$I_{res} = I - I_{bilat} \tag{16}$$

- Contrast-modified version of the output image

$$I_o^{'} = I_o + w_c \left(I_{res,s} - I_{res,o} \right) \tag{17}$$

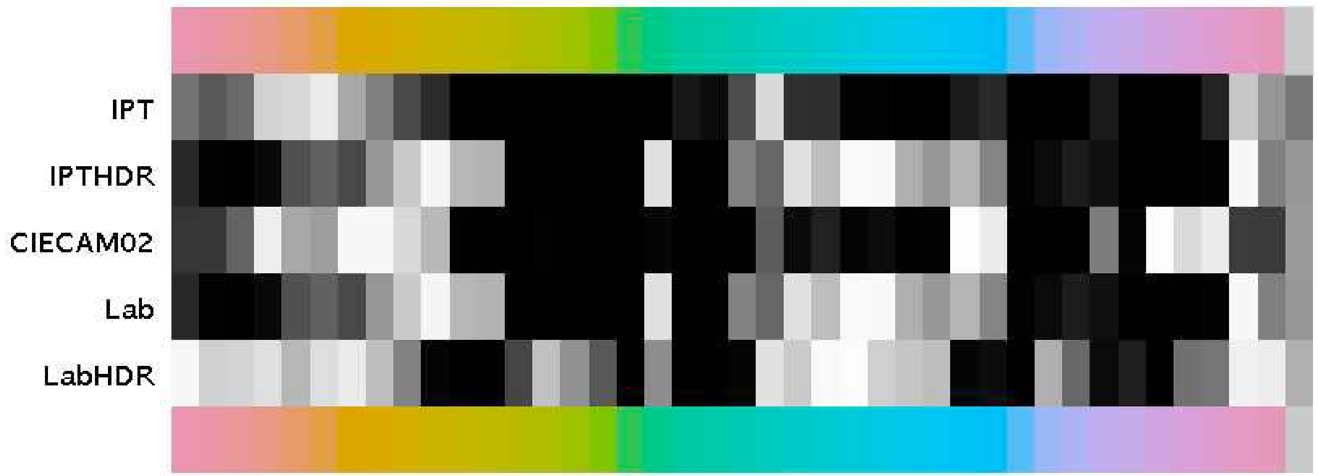

Fig. 7. Results of t-tests on hue spacing. If each Munsell hue was equally spaced from its neighbors for a given model, the row of squares would be white. Black areas indicates hues with poor spacing.

◆ Wide-Range Lightness Predictions

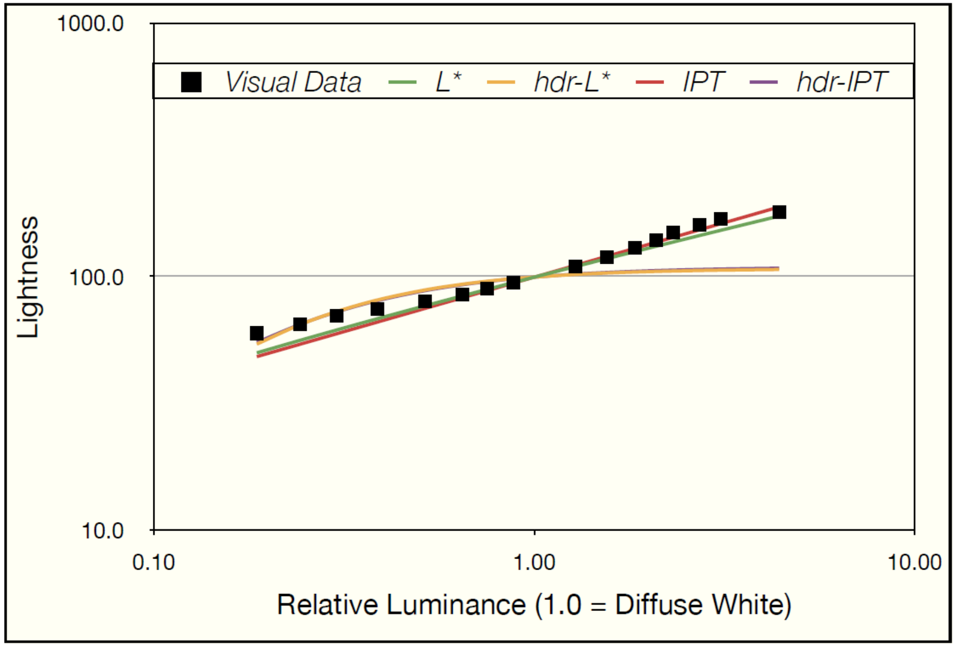

Fig. 8. Prediction of lightness scaling data in the range from L* = 60 to L* =180. Symbols are visual data and lines are model predictions. 95% confidence intervals on the experimental data are approximately the same size as the plotting symbols and thus obscured by the symbols themselves.

Conclusions

- Proposed method
  - Novel color transfer method
    - Allowing significantly better control than previous methods
    - Transferring the color palette between images of arbitrary dynamic range
    - Manipulating histograms at different scales
      - Coarse and fine features